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Twitter Sentiment Analysis: Application for Classifying Tweets with Video Games as Keywords

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Abstract

The growth of microblogging services has expanded exponentially in recent years for mining user opinions. Sentiment analysis was applied to classify Twitter posts with video game titles as keywords. An analysis of the blog history, words and sentiments associated with the blog can help reveal whether the particular game is 'violent' and stress inducing or 'non-violent' and benign.

An application was developed to collect and clean data. Naïve Bayes algorithm was applied to the cleaned data to determine the polarity of the words on the data to come to a conclusion whether, based on the words of the tweet, the particular game could be classified as 'violent' or 'non-violent'.

The results of the algorithm are analysed for accuracy, precision and recall. Deep learning models are discussed for use in future to improve accuracy.

Keywords: Twitter, Sentiment Analysis, Video Games, Gaming Tweets.

1 Introduction

Since the development of the first video game *Space War,* in 1961 at MIT, the popularity of video games and gaming has been rising, although the primary focus of the first game developed was more on the computing technology rather than entertainment (Bowman 2018). Since then , and especially during the last decade, there has been significant growth of video games due to the global penetration of mobile devices and a large number of visually appealing and interactive games were available (Green et al. 2015). As computer technology now covers every field of life, understanding its impact on a persons self-esteem and clinical implications is an important aspect (Ingram and Cangemi 2019). Analysing the effect of video games on a person's self-esteem and mental health can provide important insights. Video gaming can be quite addictive . with positive and negative effects on users.

Sentiments are a key factor in successful and constructive human-to-human relationships (Cambria et al. 2017). The terms 'opinion' and 'sentiment' are often used interchangeably. As there is a subtle difference between both, mining of the two fields means analysing people's sentiment, opinions, attitudes and reviews on products, topics and events. With the exponential growth of online review forums, community forums, blogs & micro-blogs, individuals and companies are using the opinions available on such platforms for decision-making. This helps organizations reduce costs spent on surveys and product reviews. However, with the availability of such large volumes of opinions on various forums, it becomes difficult to extract specific content and draw conclusions from a cluster of mixed opinions. It is thus essential to extract and analyse opinions on the web through the means of automated systems as it helps in reshaping organizations and businesses (Liu 2012). The key objective of sentiment analysis is to enable the use of automated tools to extract useful sentiments from a natural language, which could be later used in decision making (Pozzi 2017).

Microblogging is a very popular means of expressing sentiments and opinions. Millions of messages are posted by users daily on popular websites that provide microblogging platforms such as Twitter, Facebook, Tumblr, Reddit among others. The messages written on such websites contain opinions on various topics, life stories and even current affairs. Microblogs provide a popular, free format and ease of use compared to the traditional blogs and mailing lists. Increasing use of microblogs allows organizations to use tools to perform sentiment analysis for effective marketing strategies (Pak and Paroubek 2010).

The messages that a user posts on Twitter are termed 'tweets' and these tweets are publicly accessible to everyone on the user's profile. Twitter messages contain emojis, hyperlinks and other forms of media such as gifs, images and videos. Although the messages being written by users are restricted to 140 characters, a tweet contains essential information. People make use of the special character '#' (Hashtag) to concisely address the issue by including topics in hashtags, for example, #covid-19, # coronavirus (Murthy 2018). Esports (Electronic sports) which involves competitive gaming is like conventional sports having competitions which include two teams. 71.5 million people watched an online esports game in the year 2013 (Ingram and Cangemi 2019). During such massive video game events, millions of people post their views onto popular websites such as Twitter. Mining these user opinions is an important task for an organization or a company intending to develop a user-centred video game.

In this research study, an application is developed which can scan microblogs to determine whether a video game induces violent or aggressive behaviour. The developed application contains a sentiment analysis algorithm based on Naïve Bayes classifier model and the user interface is designed through the python package Tkinter. The application returns a score which indicates whether the game is positive (inducing positive behaviour) or negative (inducing violent or aggressive behaviour) or neutral.

2 Objectives/Research Questions

Some of the research questions are*, how does the developed application help a user make choices?* The Sentiment Analysis algorithm obtains tweets for a specific game the user entered and then classifies them whether they are positive or negative. Then the percentage of individual groups are calculated and returned, a higher percentage of negative tweets mean that the tweets contain more negative impact on users.

Twitter is a microblog; people often post updates and express thoughts about activities or their lifestyle. A sentiment score will be indicative of how the gaming community reacts to certain games. Users may not want to try games with negative score.

What is the relation of the application with gaming addiction? Since the developed application can identify whether a certain game has negative tweets related to it, it will recommend whether the game should be played or not. The user, in turn, should refrain from playing that video game, as the game that was predicted to be negative may inculcate in the user abnormal behaviour such as rage and anxiety or in the worst case cause the user to be addicted to it simply because of a highly competitive environment.

3 Literature Critique

There has been an exponential amplification in the use of platforms that provide microblogging services such as Twitter. This growth has encouraged and attracted many companies and organizations to extract opinions posted by users. Kouloumpis et al. (2011) explained in their paper, how the concepts of Natural Language Processing (NLP) such as n-gram, lexicon features, post-tagging & the features contained in micro-blogs are used for analysing sentiments by leveraging hashtags.

A basic version of sentiment analysis consists of two components: *emotion recognition* and *polarity detection*. Both these concepts are interconnected, and polarity detection is sometimes considered as a sub-category of emotion recognition. Emotion recognition has its primary focus on extracting emotion keywords as labels from the given dataset, while the job of polarity detection is to classify the keywords extracted into a binary classification. The classification output can be from categories of positive to negative, thumbs up or thumbs down, upvote or downvote, like or dislike (Cambria et al. 2017).

Twitter microblogs can be considered as a source for extracting and predicting a plethora of information or results. A significant amount of information can be extracted from Twitter that relates to future events; this functionality is extremely useful where such events are a security concern and may require physical safety. A system described by Kunneman and Van Den Bosch (2016) tends to extract detailed information of such public upcoming events in real-time.

Real-time sentiment analysis was performed by Wang et al. (2012) on Twitter data; the topic covered was U.S. presidential candidates in 2012. IBM's InfoSphere platform was used to implement the model. The training data contained 1700 tweets with labels such as sarcasm, humour, positive, negative, neutral, and unsure. The architecture of the model consisted of pre-processing steps such as tokenization and matching tweets to the candidate by checking whether the name of the candidate is present in the tweet, the sentiment model itself and visualization. The analysis consisted of a time-series chart along with the most trending words of the respective candidates.

Correlation between the market sentiment and public sentiments were analysed by Mittal and Goel (2012) for predicting the stock movements. The dataset used was Dow Jones Industrial Average (DJIA) as well as a publicly available Twitter data consisting of 476 million tweets. The output of the sentiment analysis of the Twitter data along with the pre-processed DJIA data was used for their predictive model. The moods predicted by sentiment analysis were calm, kind, happy and alert. The model obtained an accuracy of 75.56% using the Self Organizing Fuzzy Neural Networks. Further, in the section, we discuss the positives as well as the negatives of playing video games.

3.1 Benefits of Playing Video Games

A plethora of people choose to play video games rather than exercising, and some people prefer both of these combined. A study conducted in Brazil compared traditional exergame with a newfound exergame technique where a mini trampoline (MT) is utilised. The researchers concluded that MT-based exergames were more intensive than the traditional games (Rodrigues et al. 2018). The researchers measured a variety of variables such as heart rate, oxygen consumption, and positive well-being and concluded that MT-exergames can improve the cardiovascular health of individuals.

Similar research was conducted on exergame, active video games (AVG) dancing by AygÜN et al. (2018). the population consisted of 26 members, including both hip-hop dancers as well as non-dancers. Variables considered in the study were oxygen consumption, energy expenditure, respiratory exchange ratio, maximum oxygen consumption (the maximum amount of oxygen consumed by the individual during exercising). The results of the study were that a significant elevation was seen amongst the variables and that AVG dancing can be considered as high-intensity exercise.

The findings of Simons et al. (2014) were that active video games (AVG) can positively impact the weight of adolescents. The variables other than weight measured during the test, are height, waist, skinfold thickness and circumference of the hip. The main factor noted for positive impact on weight loss was due to the intrinsic motivation of the children; meaning the children engaged in the activity not because someone prescribed it but because they enjoy it. Some studies have shown that AVG could burn approximately 381 calories per hour resulting in decreasing the BMI of adolescents (Concepcion 2017).

Horowitz (2019) conducted a study of college students in Puerto Rico who had English as their second language (ESL). The study concluded that multiplayer video games assisted the participants in reducing their anxiety as well as improved their communication skills. A reaction in the participants, called game transfer phenomena (GTP) triggers thought, actions and sensations during the game which are associated with real life situations. This phenomenon is applied to learning specific content such as a second language, helping create an ideal condition for speaking by engaging the player into the game thereby reducing anxiety.

Another study conducted by Rui et al. (2013) investigating the effects of video games on cognition involved thirty-two participants. The researcher performed a double-blind trial which was randomized and controlled using the popular 'brain-training' video games, *Brain Age* and *Tetris*. These games were randomly assigned to the participants who were asked to play the game for short durations over a period of four weeks. The variables of cognitive functions including executive function, working memory, short-term memory and attention were measured pre-training and post-training. The results of the research were that the brain training game (Brain Age) enhanced processing speed as well as the working memory of the participants while the puzzle game (Tetris) enhanced visual-spatial ability and attention.

3.2 Adverse Effects of Playing Video Games

A study by Evren et al. (2019) for determining the relationship of Internet Gaming Disorder and Internet Addiction consisted of 1509 participants. All the participants were regular internet users and university students. The research considered various variables such as anxiety, depression, anger, hostility etc, to define relationships between IGD and IA. The findings of the research were that even after controlling certain variables, mainly aggression and negativity, there was still a probability of attention deficit hyperactivity disorder (ADHD) being related to severe internet addiction and internet gaming disorder.

Tian et al. (2020) studied the relationship between shyness and aggression concerning violent video games. 100 participants each were selected from a group of shy and 'non-shy' or confident Chinese university individuals. Half the participants (50) from each group with the highest and lowest scores were asked to play *Player Unknowns Battle Ground* (a popular video game in China, considered a 'violent video game') the other participants were asked to play *Sims 3* (another popular video game in China, but considered to be a non-violent video game). Once they finished playing, a reaction test was performed, where the loser was subjected to a 'sound' punishment determined by the winner. The level of sound ranged from 80db to 110db. The reaction time and accuracy were noted, and results were drawn from the study. Researchers concluded that violent video games increased the aggressive behaviour and negative effects amongst shy individuals.

Video games aside, in general, usage of computer for prolonged periods can cause headaches, neck pain, and eye strain. A study by Palm and Risberg (2007) on 1575 females and 1251 males studying in upper secondary schools analysed questionnaires and concluded that eyestrain and forearm pain was more prevalent in students using computers for more than fifty-six hours per week. The adverse effects caused, also contribute to negative microblogs and these microblogs by current users of a game will help new users make an informed decision about the game and if they should pursue to play it.

4 Methodology

An application is designed to extract key words associated with a video game from microblogging sites. Sentiment analysis algorithm is applied to provide polarity and determine whether the game is violent or non-violent.

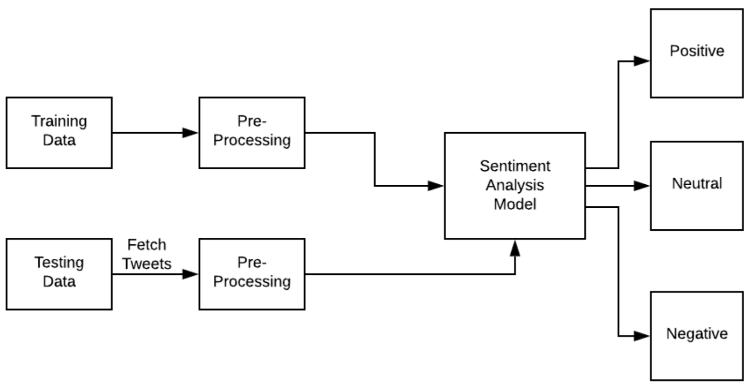

Figure 1: System achitecture.

The application architecture addresses pre-processing steps such as data cleaning and training the model to obtain the polarity of the sentiment. Descriptive data analysis through frequency count graph and word cloud helps in the analysis about the game. The process of cleaning, applying the algorithm and designing the application is explained in the sub-section below.

4.1 Data Collection

Even though there is an abundance of data on the internet, datasets for specific domains are not easily available. Some organizations may have the domain-specific dataset, but they may not be willing to share it due to commercial reasons. Thus, for training the model, microblogs from subreddit */Gaming* were used. This dataset was obtained from *Kaggle.com* which is a public repository for a variety of datasets. Users can also post their datasets, if rules regarding user anonymity are adhered to.

For test data, Twitter API was used to collect the recent 100 tweets with a keyword provided by the user. For using Twitter API, OAuth library is used which makes it easier to collect tweets for the provided keyword. Authentication is performed by OAuth with the help of Access Token Key, Access Token Secret Key, Consumer Key and Consumer Secret Key of Twitter. A handshake protocol is performed following which a certificate is downloaded leading to a PIN generation for the application to access tweets (Prakruthi et al. 2018).

4.2 Data Description

The data obtained from *Kaggle.com* for the subreddit */Gaming* has 2,81,633 rows and 16 columns out of which only the 'post' and 'sentiment' column were used. The 'post' column contains the actual writings of the user including opinions, reviews, status updates, links to other sources etc. While the 'sentiment' column contains the sentiment score of the post, as in Table 1:

Score	**Attached Sentiment**
-1	Negative
0	Neutral
1	Positive

Table 1: Labels and their Score.

4.3 Data Cleaning

To enhance the quality of the data and improve the accuracy of the model, data cleaning is a crucial task. It addresses redundant data and detects and removes anomalies from the data. Data cleaning is time consuming process as there can be a wide spectrum of inconsistencies due to the sheer volume of data (Rahm and Do 2000). The records of obtained dataset contained unnecessary special characters which would affect the model and create a bias while choosing the right sentiment for the test data. Necessary steps were taken such as performing regular expression on the records to remove the special characters.

4.4 Naïve Bayes Algorithm

Naïve Bayes classifier has been gaining popularity as it is a very simple yet effective algorithm. One assumption of the algorithm is that it considers all the attributes independent of each other. Even though such assumptions are invalid for real-world tasks, the algorithm performs better than others (McCallum and Nigam 1998). The algorithm is based on Bayes theorem along with the conditional independence assumption. Bayes theorem is stated as:

$$P(A|B) = \frac{P(A).P(B|A)}{P(B)}$$

Where, P(A): probability of event A taking place, P(B): probability of event B taking place, P(B|A): probability of occurrence of event B given that event A occurred, P(A|B): probability of occurrence of event A given that event B occurred (Saritas and Yasar 2019). Similarly, Naïve Bayes classifier can be represented as follows:

$$c_{NB} = \text{ argmax } P_{C_j} \prod_i P(a_i \mid c_i)$$

Using the above formula, a posterior probability is calculated by multiplying the probability of each class with the probability of all the features for their respective classes. Finally, argmax function is used to return the class with highest probability. Basically, calculating likelihood of each feature being positive, negative, or neutral.

Naïve Bayes has been used in the past for real-time classification using SentiWordNet by Goel et al. (2016), sentiment analysis on Facebook statuses by Troussas et al. (2013), stock prediction by Mittal and Goel (2012) and U.S. presidential election real-time sentiment analysis (Wang et al. 2012).

Before feeding data to the Naïve Bayes model, some pre-processing steps are required, which will assist the model in learning the data and reducing the program execution time.

4.5 Text Categorization

Also referred to as text classification, is the process of allocating one or multiple classes to each text in the corpus. A text classification is usually carried out in three steps which include pre-processing, learning and classification (Jo 2019). In the pre-processing step, special characters and URLs are removed from the corpus as they add unnecessary bias to the classification model. Tokenization is performed to tokenize the sentences from the corpus and words from those sentences. Stemming or lemmatization which are optional are performed to obtain the root words. Once a list of words is extracted, a 'bag of words' model which will count the frequency of each word is generated. While in learning step, a labelled sample of text converted into vectorized numerical, is fed to the classification algorithm. The model learns to classify based on the sample provided. To test the performance of the model, a test set is either divided from the training data or a new unlabelled data is provided as a test data.

4.6 Developed Application

An application is developed with the help of Python's Tkinter package in combination with machine learning techniques and NLP. The developed application takes keywords as input. These keywords are names of video games. Twitter API will fetch tweets containing the input keywords which will be the test set. Some pre-processing steps are performed on both the training and test data to remove unnecessary special characters, links and stop words. Tokenization is performed to split the sentences into words which act as an input to the algorithm. A model is created based on the training labels; this model learns how to classify certain words in the sentences using probabilistic computations. The output of the model is a list of classes: -1 for negative, 0 for neutral and 1 for positive.

The developed application can be used by anyone who enjoys playing video games and wants to check the positivity of a video game or a game community. It can be used by organizations to check how their product or a video game affects the market and whether they are performing better than their competitors. Many organizations are already aware of this concept and have been using this for mining user opinions. These opinions will act as feedback and can be used to enhance their existing video games or products.

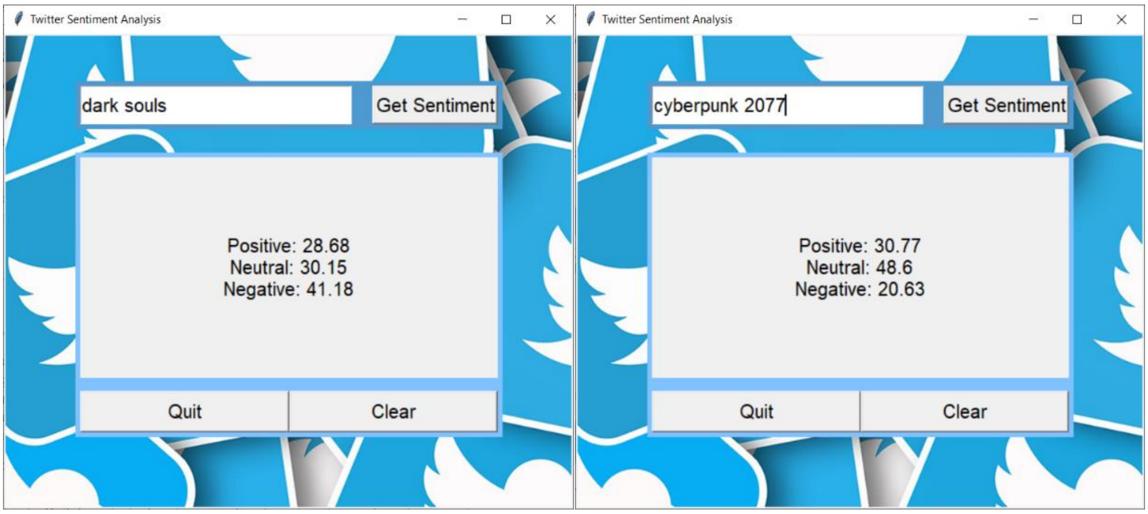

Figure 2: Keywords of the developed application.

Figure 2 describes sentiments for two keywords which are popular video games. “Cyberpunk 2077” is due to be released later this year (2020). While many potential users will be willing to download the game as soon as it is launched, some users will want to check the reviews to determine whether the video game is good enough for them to play or whether the video game contains graphic images and high levels of violence. With the help of the developed application, a user can easily interpret whether the video game contains positive or negative aspects, from the sentiment score predicted by the application.

4.7 Experimental Data Analysis

For the analysis of the data, descriptive statistics as well as inferential statistics were performed on training as well as test dataset. From the training dataset, the first 1,500 records were chosen to perform the visualization for faster computation time, as well as the test data set fetched from the Twitter API for the keyword ‘valorant’, for a popular video game which was recently released. The test data contained 250 tweets which were classified by the model. The most common words, as well as frequency, will be fetched out from the two diverse datasets. Both have textual sentences and sentiments in terms of positive, negative, or neutral.

Figure 3: Most common words for training set.

Figure 3 above displays the 40 most common words from the dataset. There are some negative as well as positive words in the list. Maximum use of the specific names of the game is made by the users who wrote the post; which indicates that the users had the name of the game included in the hashtag or the context.

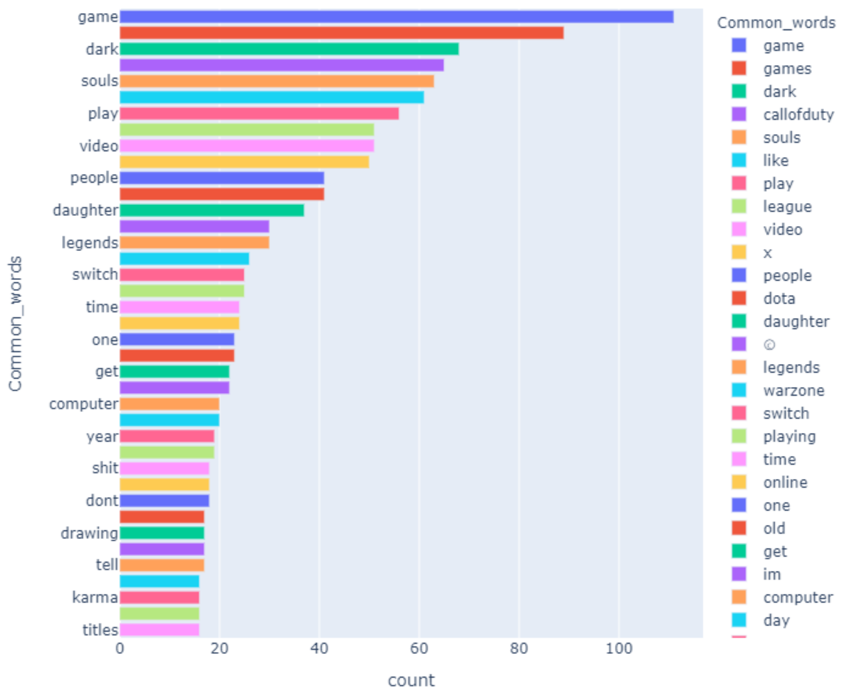

Figure 4: Frequency count for the training set.

The frequency count of the most common words in the training set described in Figure 4 above. The frequency count provides useful insights about the users. The common word 'computer' suggests that users like to play computer games more rather than on consoles. The mention of the game names suggests that these games have a much bigger community or possibly some of the mentions may be a popular game.

Figure 5: Word cloud containing the most common words for the test set.

Figure 5 contains the most common words for the category 'valorant', this dataset containing 250 words is fetched using the developed application for sentiment analysis from Twitter API. At first glance, some negative words stand out. However, as seen in Figure 6 below, the ratio of positive words is much higher than that of the negative words.

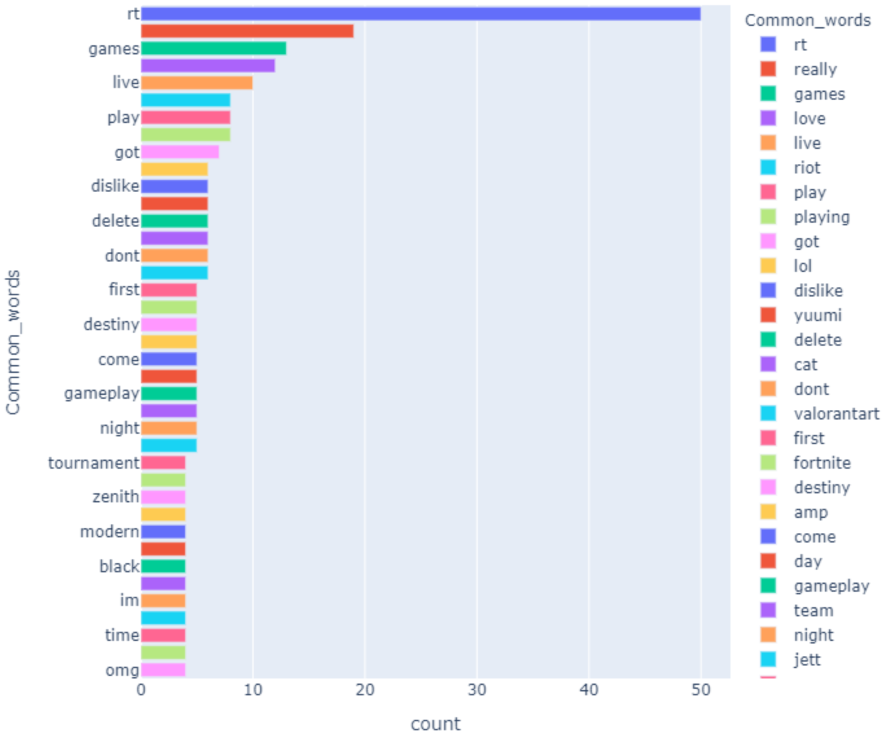

Figure 6: Frequency count for the test set.

5 Metrics

To evaluate the developed application, average execution time was calculated along with accuracy, precision and recall. To calculate the time taken to run the algorithm, three iterations were carried out to generalise average the execution time results. Average was computed on the instances to get the final runtime of the algorithm.

Iteration	Time Taken (seconds)
1	5.609
2	7.203
3	7.813

Table 2: Execution times.

The average time taken to execute the program is 6.875 seconds since we have a medium-sized dataset, the time taken to learn all the features by the model is time-consuming. Application quality is not dependant on the accuracy results alone, but several other factors such as time and usability are ALSO crucial. Classification report of the algorithm was computed, the algorithm on training data set had an accuracy of 60.5%, whereas the precision was 57% and the recall at 64%. The developed application does a decent job of classification even though some approaches such as the one from Mittal and Goel (2012) have achieved 75.56% accuracy in terms of classification.

6 Results

Various keywords were entered as input into the application for noting down the percentages obtained for analysis. Similar word neighbours for the keywords entered were also found using topic modelling. Benchmarks for the developed application after analysis suggest that a higher percentage of negative sentiments results in a large number of negative words into the set of tweets. A lower number for the negative sentiments is preferred, whereas higher the number of positive sentiments the better the reviews and the tweets consisting of those keywords will be.

Keyword	Pos (%)	Neu (%)	Neg (%)	Neighbours
Pubg	26.66	63.80	9.52	Legends, etc, Instagram, Twitter, mobile, pubg, kills, win.
Minecraft	17.24	35.17	47.58	Joke, itæs, isnæt, aotakeo, sweetest, thing, rt, just
Call of duty	23.88	25.37	50.74	Duty, more, call, out, anxious, while, playstation
Elder scrolls	28.57	42.28	29.14	Elder, scrolls, franchise, theme, loot, combines, fav, dark

Table 3: Keywords with sentiments and their topic neighbours.

6.1 Comparison with Deep Learning Models

Research by Hassan and Mahmood (2017) for sentiment analysis using Convolutional Neural Network (CNN), trained on two different datasets provided by Stanford achieved an accuracy of 85.7% and 86.4% respectively, with the first dataset consisting of 5 classes and the second dataset with 2 classes. Their research focused on character level and sentence level embeddings to tackle the problem of short texts using Character to Sentence Convolutional Neural Network (CharSCNN), and Sparse CNN (SCNN). Another similar method of predicting polarities at message as well as phrase level given by Severyn and Moschitti (2015), a three step procedure is followed where at first a neural model is utilized for initialization of word embeddings, the produced embeddings are refined using a CNN and lastly the obtained word embeddings with other parameters are used to train a supervised corpus. Their devised approach produced an accuracy of 84.79% at phrase level and 64.59% at message level. An ensemble approach of combining Long Short Term Memory networks (LSTM) and CNN was adopted by Minaee et al. (2019). The model was trained on Stanford Sentiment Treebank2 (SST2) and Internet Movie Database (IMDB) data set. Words in the review dataset were represented using Glove embedding, which is then fed to both the models, average is calculated of the obtained results for final predictions. The accuracies achieved for both the datasets were 90% for IMDB and 80.5% for SST2.

7 Findings and Discussion

From the analysis and results section is it clear that the tweets contain mixed sentiments, both positive and negative. Although the use of words such as "dark", "kills" are popular and the main reason for the application to set the specific tweet as negative. From the accuracy computed we can say that the developed application lacks the accuracy to predict correctly, however a major factor in predicting lies in the dataset. Even though the training dataset was not from Twitter, the model performed well. Another factor for the low accuracy percentage is the number of automated bots on twitter, which constantly spam the same messages or may post a review about a product. The reviews posted by these bots are biased to a specific organization in order to 'bump up' their sales value. Sometimes an update of a popular game may cause the game to crash causing an uproar amongst the community on Twitter, resulting in negative sentiments.

From Figure 4, we see that positive words such as 'love', 'live', 'play', etc are the most used words indicating that not all games are violent. Some games urge the users to post good tweets. This may be a factor that the game is positive, and the user enjoys playing the game. In some cases the game could also be a stress reliever.

On the contrary, as researched by Tian et al. (2020) violent video games *do* have an impact on one's physical wellbeing and increase aggression, causing the players to rage. The developed application focuses on avoiding such issues by predicting whether a game is positive or negative. Competitive gameplay could also result in online gaming addiction (Evren et al. 2019). Table 3 has a list of games from which three of those games can be considered violent video games and come under the category of competitive gameplay. From the neighbour words of the keywords we see a that several negative words are associated with the games. All the games in Table 3 have high percentage of negative sentiments, while Figure 2 portrays a similar scenario where the game has a high frequency of negative words in a tweet related to the keyword.

8 Future Work

Future work could involve improving the accuracy with a larger and more accurate dataset. Redesigning the model with deep neural networks with fuzzy logic could also improve prediction accuracy as a tweet can be positive as well as negative. The number of classes could be increased from two to possibly more than five by adding classes based on mood of the user. A game reviews dataset would provide better insights but may not be suitable for the topic sentiment analysis as reviews contain ratings of users about the video game with the perspective of reviewing them, whereas a social media post may contain user emotions about a game and will not be fixated to a topic of review.

9 Limitations

Sentiment analysis can be conducted in multiple ways. The current application is implemented with a 'bag of words' model; however, a better approach towards the same solution would be term frequency-inverse document frequency (tf-idf). Since tf-idf calculates the importance of the words by weighing each word according to the document with the occurrence of the word in the document itself. Training the model with emoticons dataset to further improve the accuracy as vast number of people frequently use emoticons in their posts. Implementing 'parts of speech' (POS) tagging in the pre-processing stage and extracting phrases for topic modelling so that groups of positive and negative topics can be clustered together. Such clustering will help analyse the similarity of topics and the underlying relationship can be studied.

10 Conclusion

Twitter is a popular social media microblogging service; analysing sentiment is a crucial task for organizations and companies. From the research conducted, it was possible to examine the positives and negatives of tweets containing video games as keywords. An application was developed to support the examination which performed sentiment analysis. This developed application will be helpful to users and parents concerned about young people playing aggressive and violent games and can support them to play games that have more positive sentiments. The application will be useful to organizations to gain an understanding of the users of their video games. The underlying cause of why tweets are negative or positive was studied and analysed, keeping in mind the accuracy of the algorithm.

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